Drivers of Retention in Online Degree Programs

Empower degree faculty and students to make the most of Coursera's for-credit learning experiences through new quantitative insights

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Executive Summary

We see a variety of factors driving student retention in degree programs offered on the Coursera platform. The following are actions universities can take to bolster their students' likelihood of staying in their programs:

Build on open content success

Recommend relevant open courses on Coursera. Students who complete an open course are 12% more likely to persist in their degree. Those who take open courses that stack into the degree are 3% more likely to remain in their programs.

Set students up for a strong start

Provide resources, office hours, and one-on-one question answering to help students submit their first assessment successfully, which increases their retention in the program by 6%. Performance is a strong indicator of students' later persistence, with first-term grades emerging as especially critical.

Include staff grading

Boost motivation through expert grading and feedback. Having at least one staff-graded assessment drives a 6% increase in student retention.

Encourage frequent learning

Use techniques like short videos and smaller assessments throughout the course to help ensure students return frequently to the degree courses. Having students learn across more days leads to a 5% gain in retention and is a more significant driver than total learning time.

Design hands-on projects

Keep students progressing with hands-on projects where they can apply their new skills. Across writing, coding, and creative projects, these opportunities drive 3% greater retention. A final project is a great opportunity to provide this type of hands-on project and culminating experience for the course.

Use practice opportunities

Include ungraded assessments for low-stakes testing and to further students' understanding. Having practice assessments drives a 2% increase in student degree retention.

Background

The Coursera platform has become a hub for leading universities to build and offer their online degrees to an eager audience of individuals worldwide. From the activities of thousands of students enrolled in our university partners' degree programs, we are able to derive new insights on how individuals are engaging with online for-credit courses, what helps them succeed, and which activities most drive their retention. Throughout this report, we offer data-driven best practices for driving greater retention in online degree programs.

Our university partners have incredible expertise to share with degree students around the world, and we at Coursera are here to help empower these faculty and staff to create high-quality, online learning experiences. These quantitative insights can help universities and students achieve their degree goals. Before exploring what drives retention, here's a quick look at who is enrolling in our partner universities' degree programs on Coursera.

Degree Students on Coursera

Online degree students tend to be older than on-campus degree-seeking students, even in bachelor's degrees. Degree students on Coursera tend to have more work experience and are more likely to be actively employed. We see a diverse, global audience attracted to these degree programs. In fact, existing degree students are joining from more than 90 countries. In total, 17,960 unique individual students from 19 different degree programs comprised the sample for this report.

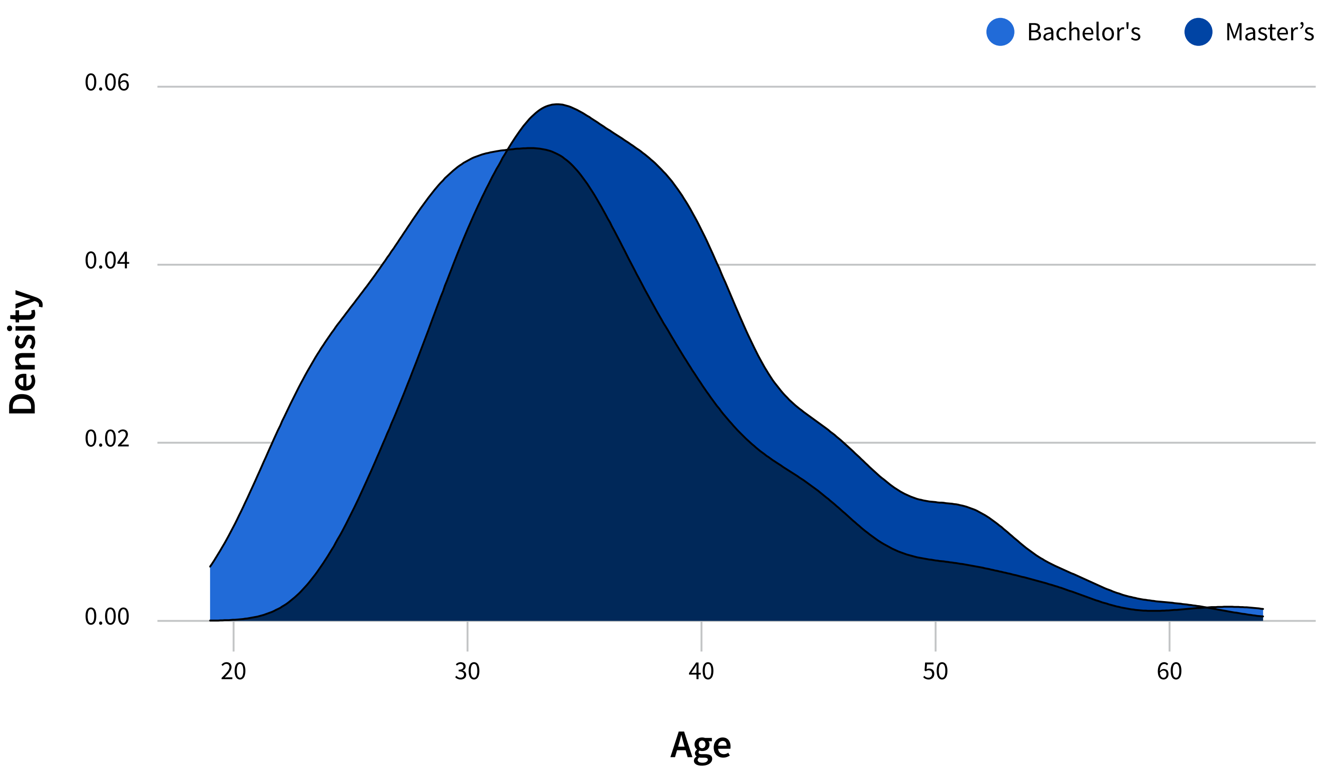

Figure 1 Age Distribution of Degree Students on Coursera

Focusing on Retention

The success metric that we seek to understand in this report is the first-year retention rate. We define first-year retention as a student who is actively enrolled in coursework in the term that starts one year after their first term of enrollment. To understand the earliest indicators of retention likelihood, we centered on activities and behaviors in each student's first term of enrollment. For example, for students starting in the fall, we examine their degree course experiences in the first term until winter break and then assess if these same students are active in the program the following fall term.

First-year retention is both a university-recognized indicator of success and strongly correlated with final degree completion. Across our data, we see that students' first term in a degree program is strongly predictive of their success throughout the program. Regardless of the degree program structure and graduation criteria, one-year retention successfully differentiates students who are on track to graduate from those who are not. Thus, this first term is the most crucial period to intervene and assist any struggling students. Plus, by focusing on first-year retention, we can include a larger sample of students, including cohorts who are 18 months into a degree program, many of whom are not yet eligible to graduate.

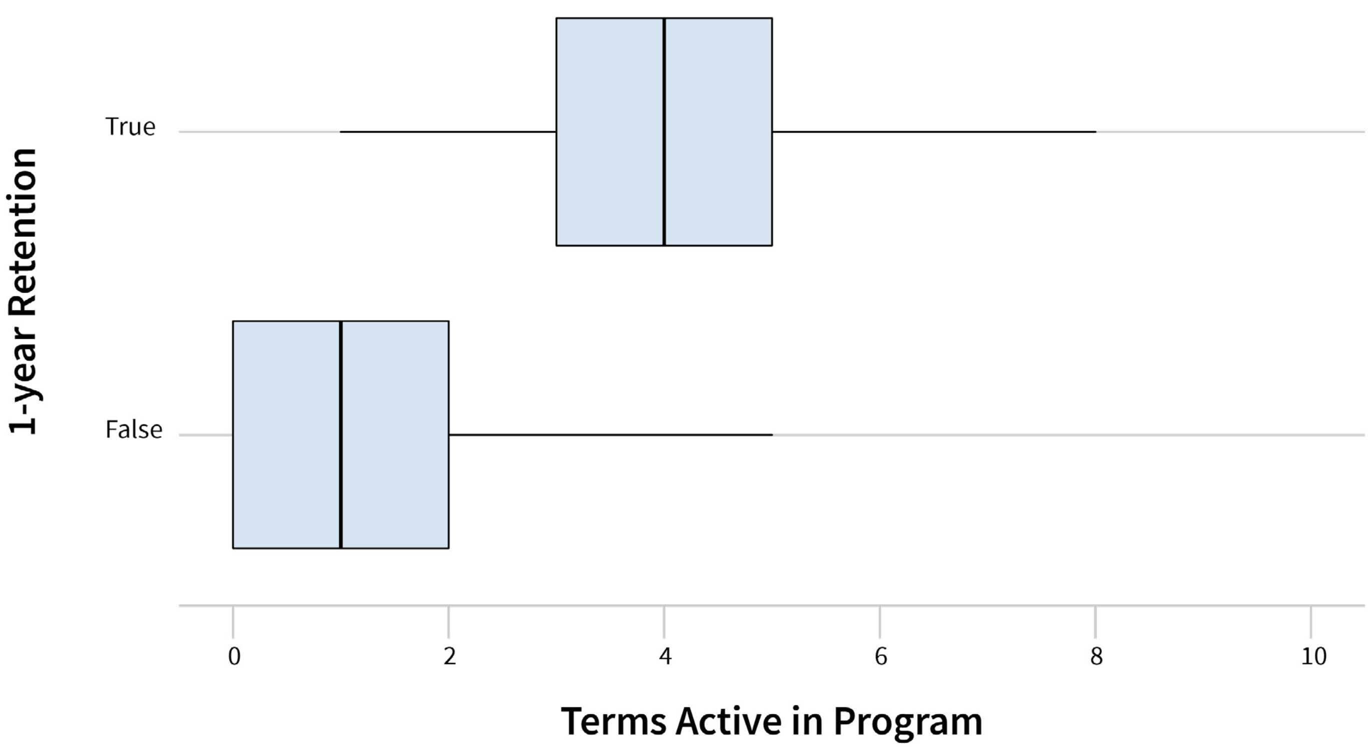

Figure 2 First-Year Retention Captures the Variability of Students' Overall Terms Active

Quantifying Drivers

Throughout the report, we use controlled regressions to isolate the impact of potential drivers on first-year persistence. Since each potential driver is observed on a very different scale, we need to standardize. Thus, we quantify the impact of each driver as the percent difference in model predictions when the driver variable is perturbed from its 25th percentile to its 75th percentile, holding all control variables at their true distribution in the dataset. This result can effectively be thought of as the average impact that a driver has on first-year retention when changed from the lower end of its distribution to the higher end. We believe that these alterations fall in the range of reasonable actions that either instructors or learners can take to enhance the quality of the learning experience. For more complete details, see the Technical Appendix.

Open Content Drivers

Learners' activity in open content on the Coursera platform can influence their later success in full degree programs. Completing Open Content is a strong driver of degree retention but simply enrolling without completing is a detracker of later degree retention. On the other hand, stackable open content, meaning it shares activities with the degree courses, has a very similar effect on later degree retention whether students are only enrolling or also completing.

If a learner has completed at least one open course before starting the degree, they are 12% more likely to persist in the degree program

Open Course Completions

One of the strongest drivers of student degree retention is previous successful learning experiences on the Coursera platform. If a learner has completed at least one open course before starting the degree, they are 12% more likely to persist in the degree program. These learners with at least one open course completion have demonstrated the motivation to make it through an online course, familiarity with the Coursera platform, and prior experience making time to learn in their busy schedules. We have seen in previous analyses (Drivers of Quality in Online Learning, 2020) that making learning a habit and building learners' confidence can increase course retention. Additionally, this strong driver highlights the benefits of Coursera's robust ecosystem: with millions of open course completers, the Coursera community has an abundance of learners poised to retain in online degree programs. These learners have already demonstrated their motivation and persistence.Having students learn across more days leads to a 5% gain in retention and is a more significant driver than total learning time.

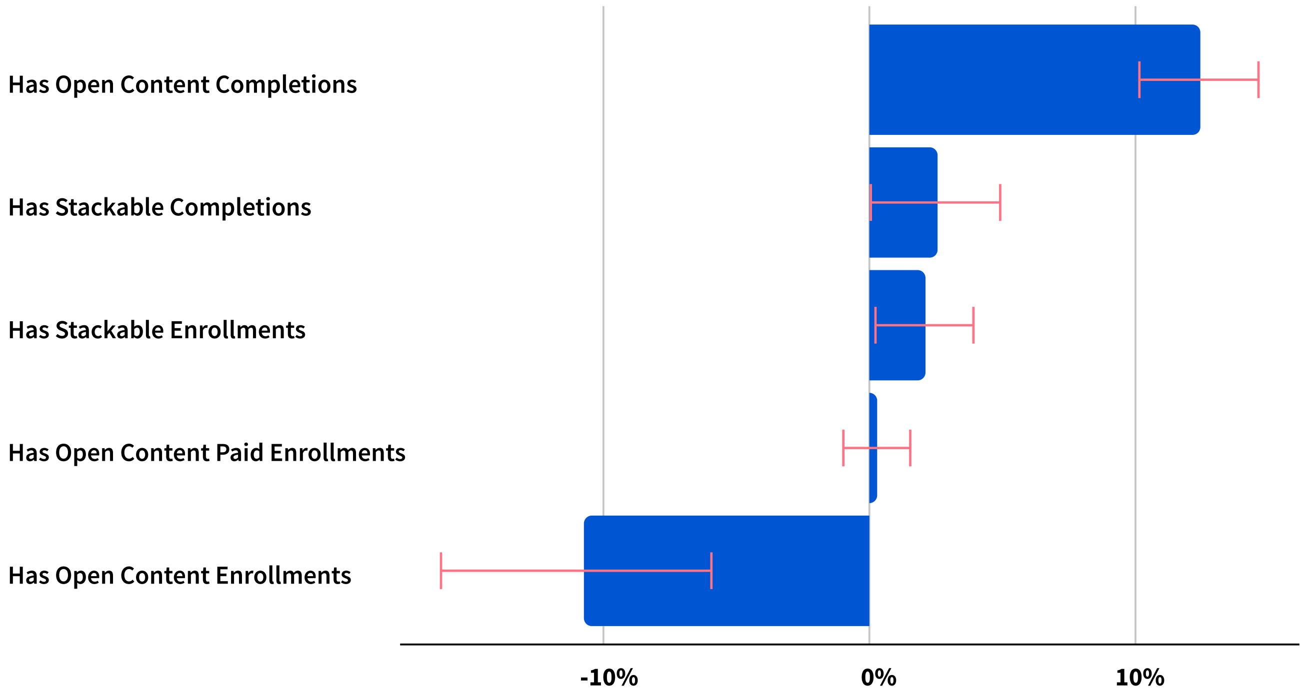

Figure 3 Open Content Engagement Effect on Degree Retention

Stackable Open Courses

The next largest driver from open courses is taking content that explicitly stacks into a degree program. For this analysis, we defined stackable open courses as those where at least 30% of the learning items are shared with a for-credit degree course. We see a 3% lift in later degree retention across both enrollees and completers of stackable open courses. This stackability strategy allows learners to familiarize themselves with the university, their instructors, and the material. By starting open courses that stack into a full degree, learners can determine if a program aligns with their interests, prerequisite knowledge, and future goals. Often, completing the entire open course may not be necessary for assessing these criteria of fit and focus. Through this open content, learners can try a preview before they start a full degree and increase their likelihood of retaining in the later degree program.

Open Course Enrollments

Prior enrollments in open content when the learner has never completed have a neutral or negative effect on later degree retention. A learner paying for access typically indicates an intention to progress through the material, take the assessments, and earn the final course certificate. However, more paid enrollments when the learners do not go on to complete the open course are not beneficial for students' later retention in a degree program. When students are not paying but simply enrolling in open courses, we see a negative effect on later degree retention. This finding suggests that the selection of a few courses to make progress in prepares students better for the focus and persistence needed in their later degree terms. Taken together, we can see how simply enrolling in open content is insufficient preparation, when considering later degree persistence. For a university partner, building stackable content into your degree can help not only boost interest and application submissions but also strengthen the later retention of those who do enter your for-credit learning experience.

Course Structure Drivers

While different subject areas and skills often require varied forms of instruction and practice, pedagogy insights can still inform how online degree courses are structured. We at Coursera keep our course design recommendations broad and flexible so that instructors have the autonomy to create the materials they know will be best for the specific subject area and skills they are teaching. University faculty bring immersive subject matter expertise, and we aim to complement that with online teaching knowledge and research they each can apply to their unique courses. In this section, we explore the quantitative trends on enhancing assessment design, creating powerful projects, and aligning coursework with students' busy lives.

Graded Assessments

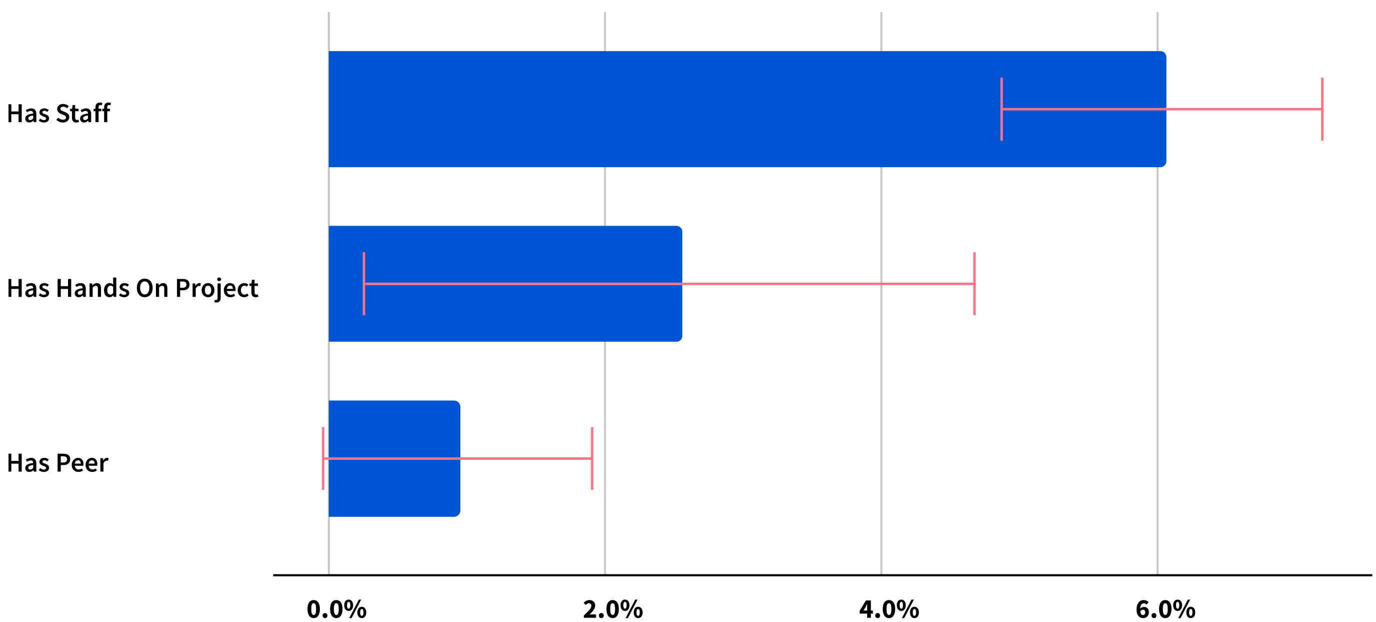

Figure 4 Different Graded Assessment Types Effects on Retention

Assessments are the core of a degree program, with instructors, students, and staff often spending the majority of their time on the summative learning experiences within each course. On the Coursera platform, we see that degree courses with at least one staff-graded assessment have 6% higher retention rates. Students are eager to receive tailored expert feedback, with degree students on Coursera consistently rating staff-graded assessments as one of the most valuable aspects of the coursework. Staff-graded assessments can provide motivation to continue in a course and offer important guidance to enhance students' understanding. Even in large courses, this moment of personalized feedback in staff-graded assessments mimics the benefits of individualized tutoring and can have meaningful implications for students' retention one year later.

Hands-on assessments emerge as a key driver of student retention, corresponding to a 3% lift

Furthermore, hands-on assessments emerge as a key driver of student retention, corresponding to a 3% lift. These hands-on assessments can include programming, staff-graded, peer-review, graded discussion prompts, and team assessments, all of which are open-ended opportunities to demonstrate new skills. With many degree students on the Coursera platform looking for career impact, these hands-on assessments provide the type of industry-relevant projects they desire.

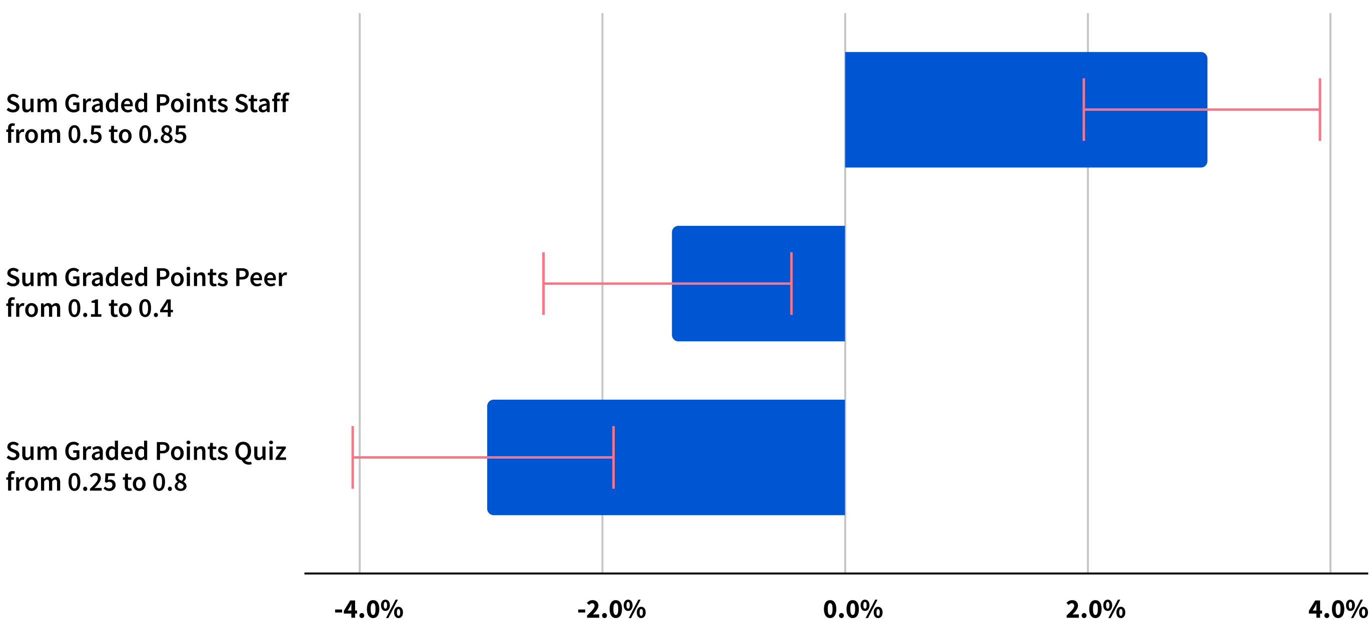

Figure 5 Course Grade Share by Assessment Types Affects Retention

Having assessments reviewed by peers appears slightly beneficial for student retention. However, when a large percentage of students' grades come from peer-reviewed assessments, motivation decreases, and students are significantly less likely to persist. Quizzes show the same pattern; while they are useful for quick tests of students' knowledge, quizzes should not be the main contributor to students' overall grades. Retention requires a healthy mix of assessments and the inclusion of open-ended projects receiving expert feedback.

Practice Assessments

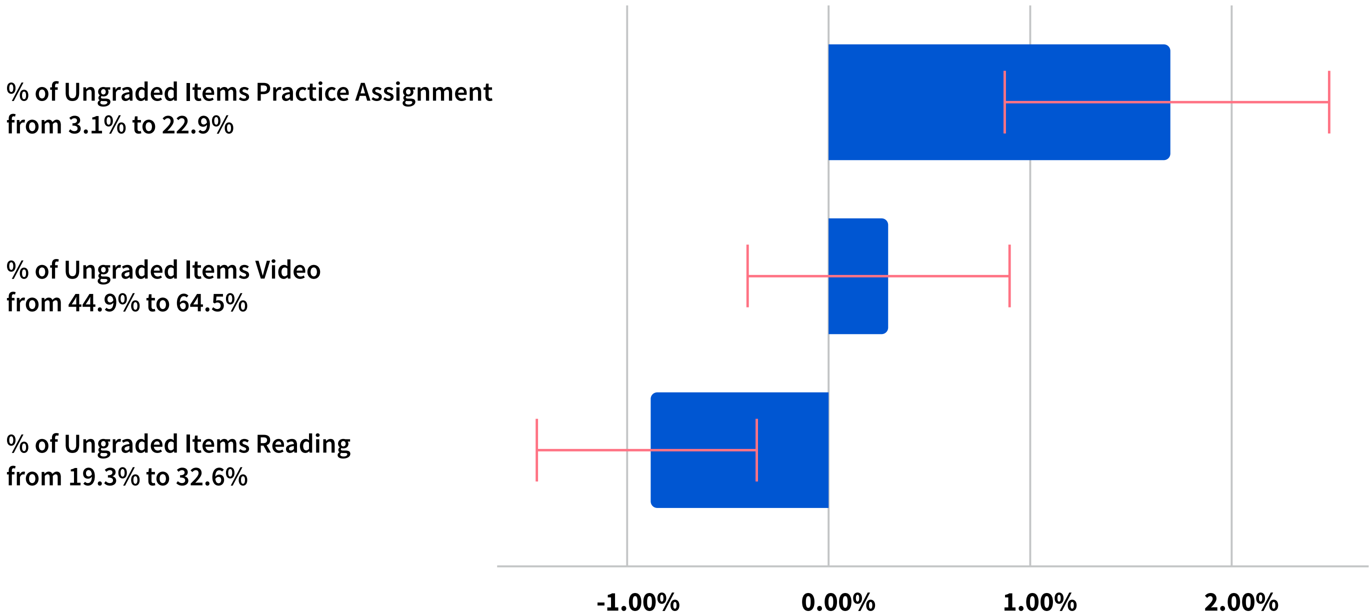

Figure 4 Ungraded Course Activities Effect on Retention

It is important to explain new concepts but often even more useful to provide low-stakes practice opportunities for students to test their understanding of those concepts. Ungraded assessments show a 2% increase in student retention, while video lectures are more neutral, and too many readings can have a negative effect.

It is important to understand that the metrics in this section are constructed to be zero-sum. In other words, increasing the share of practice assessments means decreasing the share of video lectures and readings. Thus, while creating engaging hands-on practice assessments typically takes more time, this substitution instead of more readings can be incredibly valuable for degree students.

Skills are built through these hands-on and practice activities. Just as we saw in earlier research on the Drivers of Quality in Online Learning (2020), hands-on experiences and practice opportunities drive persistence and stronger learning outcomes. Mirroring that earlier work, more practice can help students continue in their degree program.

Ungraded assessments show a 2% increase in student retention, while video lectures are more neutral, and too many readings can have a negative effect

Preparing for Projects

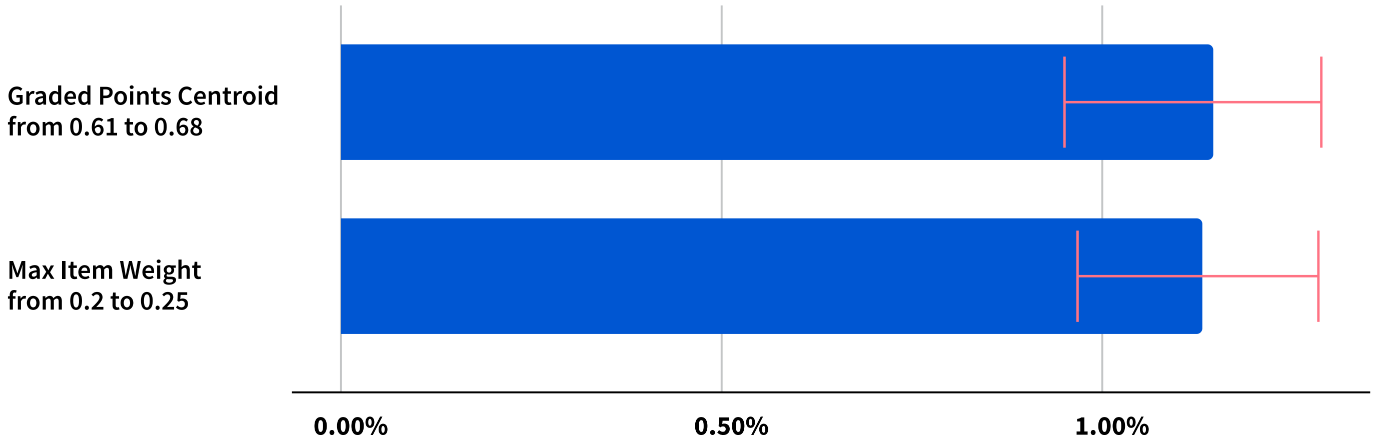

Figure 7 Course Grade Distribution Effect on Retention

For the overarching course structure, it can be beneficial to have a culminating larger project towards the end. The “weekly centroid” metric is a measure of how many weeks into a course the bulk of the graded material is located. A smaller number here means assessments are more evenly distributed while a larger number indicates the presence of a larger final project. A final project can motivate students to persist and provide industry-relevant assessments with the opportunity to apply different skills from across the course in a single submission. On-the-job tasks rarely require only one skill in isolation, and these larger, end-of-course projects can mimic the authentic activities that careers often demand. Additionally, these projects can become part of a student’s public portfolio, showcasing to employers that they are capable of applying a skill in practice, not just understanding it in theory.

While large, hands-on projects provide useful experience in real-world tasks, they can also be overwhelming. Course designers should not wait until the end of the course to introduce this larger project. Instead, instructors can orient students to the broader goal at the start of the term and build in weekly scaffolding to help prepare students for this final project. Providing milestones breaks up larger projects into more achievable pieces and ensures more consistent time needed per week throughout the course. Adding submission points and feedback throughout the course can make the final submission more achievable and set up students for success.

Course Pacing

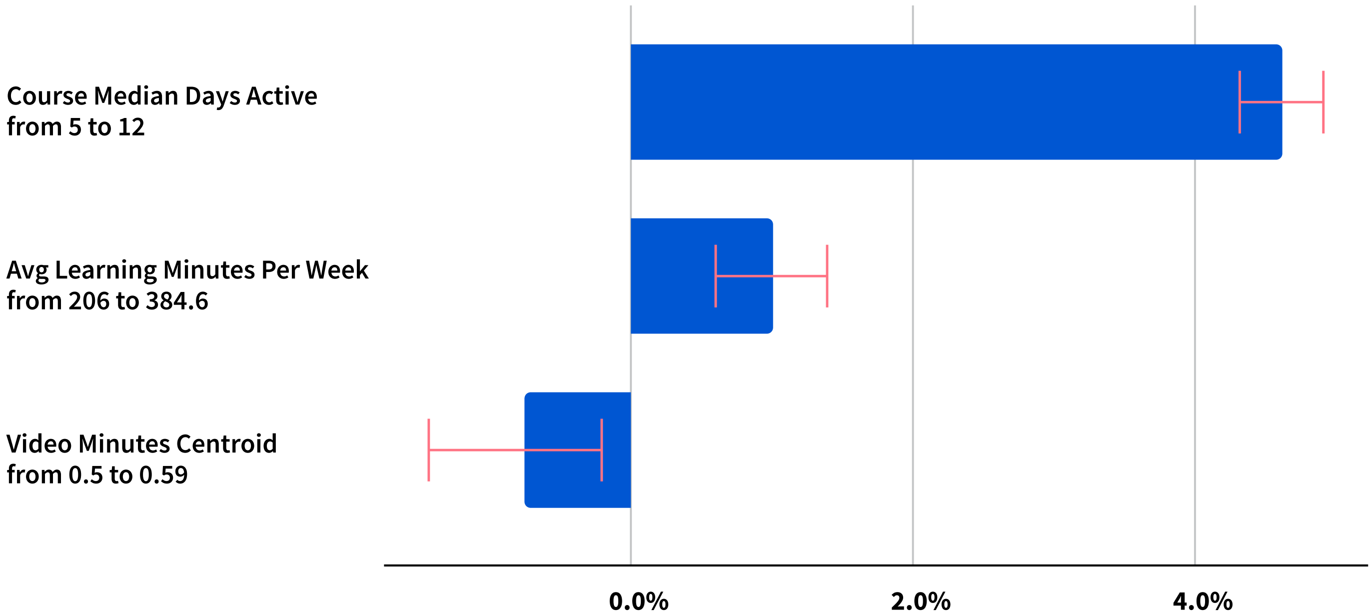

Figure 8 Course Learning Patterns Effect on Retention

At the course level, when degree students, on average, are spending more days actively engaged in the materials, we see higher persistence. Designing degree courses to encourage frequent engagement helps students develop beneficial learning patterns and return more often, increasing retention by more than 4%.

Weighting lecture time towards the beginning of the course and more assessments toward the end is a solid design strategy. This method keeps the overall learning time needed per week relatively consistent, while also scaffolding more at the beginning and having more hands-on projects towards the end.

Designing degree courses to encourage frequent engagement helps students develop beneficial learning patterns and return more often, increasing retention by more than 4%

Student Behavior Drivers

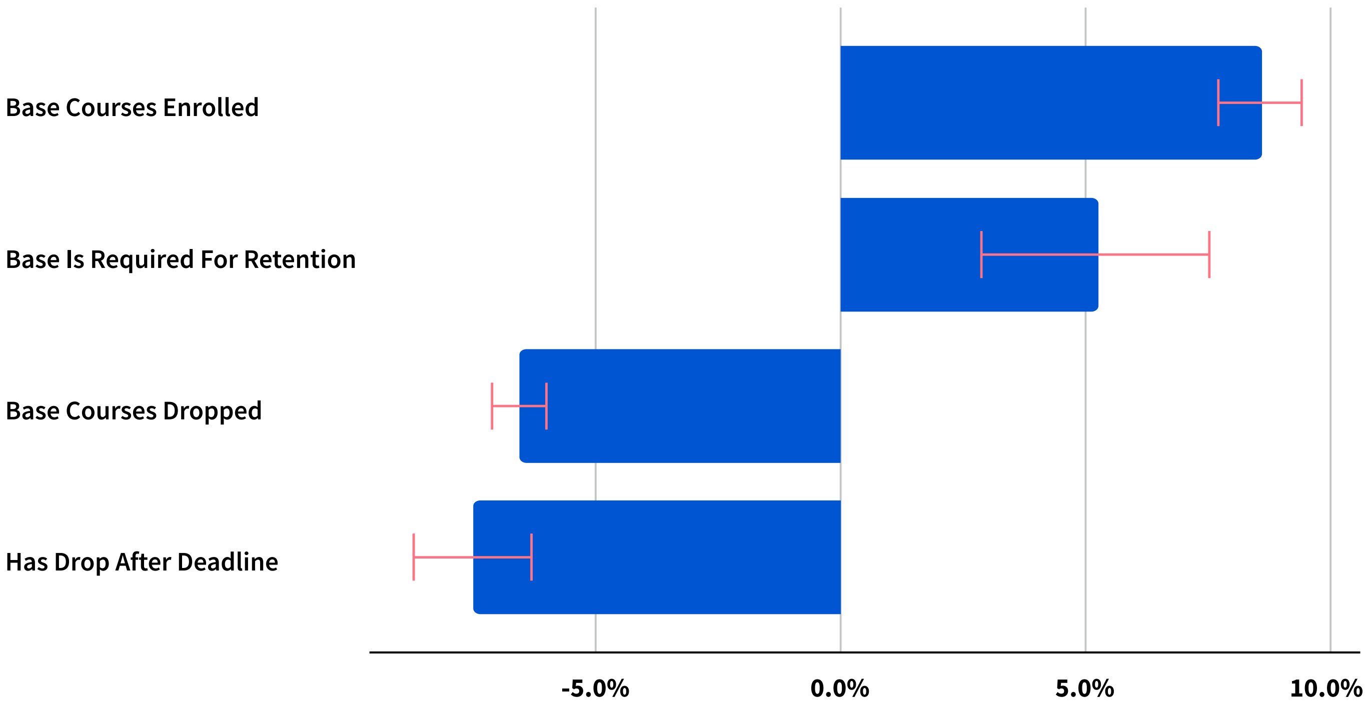

Figure 9 Student Behavior Effects on Retention

Performance and Course Load

Student behavior is one of the largest drivers of student degree retention. However, with program and course level design decisions often directly affecting students' behavior, these drivers are not beyond the control of degree educators.

Taking on full course-loads (rather than part-time course-loads) in the first term in a program improves year-one persistence by about 8%. While it is difficult to separate out the effect of students with the most demanding schedules, universities should consider how to support students by designing achievable pathways through the degree.

Dropping one course in a degree program is associated with a decrease in persistence of about 7%, and dropping after the drop deadline is associated with an 8% drop in persistence. Greater guidance on course load and overall degree pathway planning is one way universities can assist their new degree students with this often daunting task of deciding what courses to take when.

Learning Activity

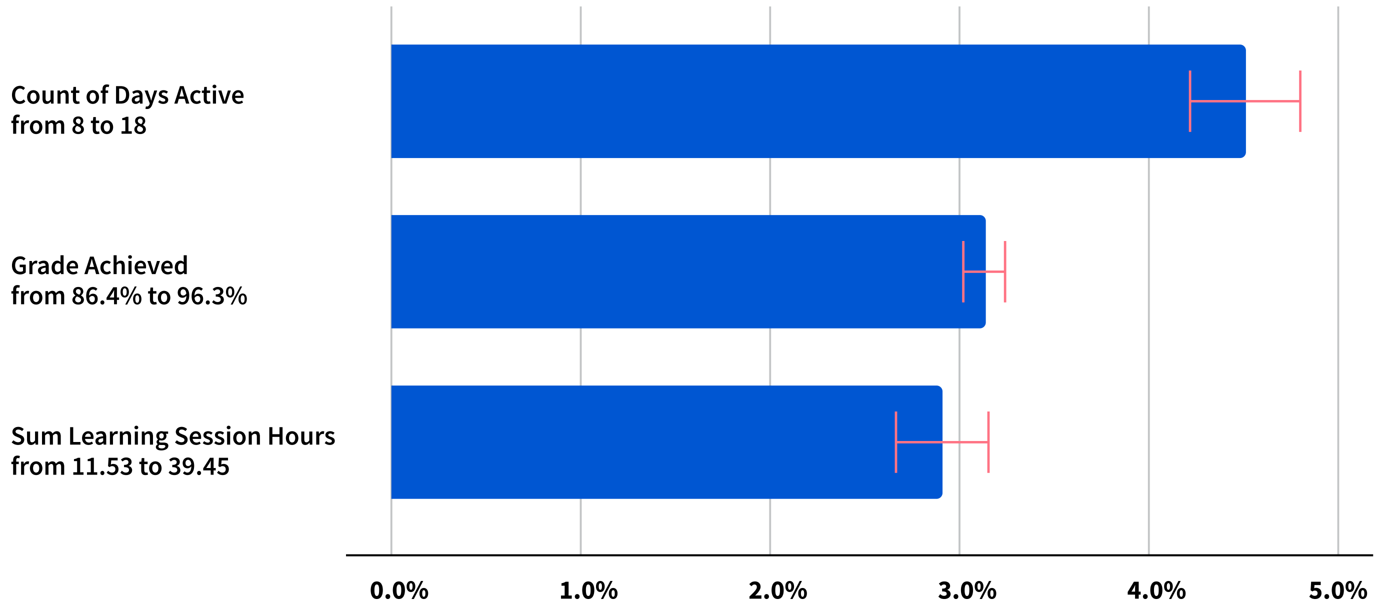

Figure 10 Individuals' Learning Patterns Effect on Retention

Consistent student engagement time per week corresponds to higher student retention rates. Most degree students on Coursera are working full-time and must balance their degree coursework with their home and family responsibilities as well. Creating consistent expectations of how much time per week they need to carve out of their busy schedules can help set up degree students for success.

Student grades achieved are key indicators, suggesting interventions that target students falling behind may be especially useful at the beginning of the program. Raising students' grades from 86% to 96% is associated with a roughly 3% increase in first-year persistence in online degree programs. While simply making the assessments easier is likely not the optimal path, providing additional clarity on expectations, grading criteria, examples, and common mistakes all are beneficial strategies.

Mirroring similar research findings in the open content setting, degree students are more likely to retain with more days active, as opposed to more time over fewer sessions. Making learning a habit is more important than carving out larger chunks of time to try and make progress, with more days active linked to a 4% lift in retention. While open courses and for-credit programs have certain differences, we see that setting up learners for success in online settings revolves around clear expectations, consistent learning time, and chunkable pieces of material.

Making learning a habit is more important than carving out larger chunks of time to try and make progress, with more days active linked to a 4% lift in retention

Strong Start

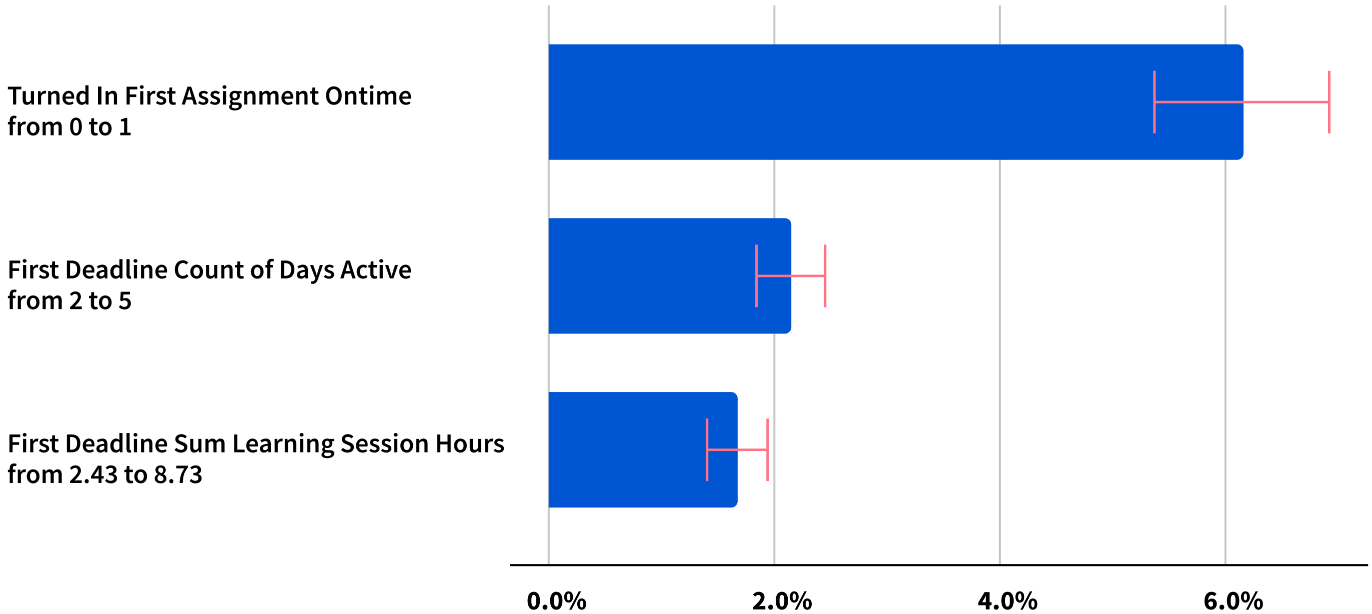

Figure 11 Beginning of Course Learning Patterns Effect on Retention

Providing support on the very first submission is crucial, so students have the opportunity to start strong. Turning in the first graded assessment and passing drives a 6% increase in overall degree persistence. As students are working towards this first deadline in their degree journey, the number of days active is more critical than learning time. While it can be tempting to tell students they need to spend more hours on the platform, it is frequent and consistent learning behavior that correlates with long-term success. For-credit courses should be designed for shorter, recurring engagement so that learners return frequently, right from the start of the degree program.

Overall, students need to get off to a strong start with both performance and pacing, achieving high early grades and staying up to date with their degree deadlines. For universities, it is crucial to intervene early with at-risk students since the first term so strongly correlates with students' continued success in the full degree program.

Turning in the first graded assessment and passing drives a 6% increase in overall degree persistence

Looking Ahead

At Coursera, we are focused on not only conducting research but also putting these new learnings into action. Looking ahead, we are committed to updating our Degree Student At-Risk models to incorporate these additional quantitative drivers of retention. Adding nuance to these machine learning models improves the accuracy and can help alert partners to when and with whom they need to intervene. Human assistance for struggling students is often crucial, and we at Coursera can aid in directing those resources to enable successful degree programs at scale.

Additionally, new data dashboards will examine how stackable content builds into the overall degree learning journey. By tracking how individuals are moving through open courses and into your degrees, we can unlock greater insights for our partners on the metrics and power of stackability.

The teams at Coursera want to empower our world-class educators to provide high-quality degree programs for students globally. These new insights can pave the way toward more efficient and effective designs, elevating faculty's online teaching to new heights.

Technical Appendix

Overview

The Drivers of Retention in Online Degree Programs Report (DRODPR) analyzes data from 17,960 students in 19 online degree programs hosted on the Coursera platform. We use regression analysis to exploit variation in student behavior and partner course design to measure the impact of various drivers on the key outcome of first-year student retention.

Regression Methodology

To reduce bias in the estimates presented in this paper, we maintain a standardized analysis methodology throughout this report. The goal of this methodology is to describe the distribution of a particular driver of retention and then identify the most actionable ways for instructors to influence it when designing or teaching in an online degree program.

We analyze each driver using an appropriate dataset, which is specified to ensure we are drawing conclusions from reliable and meaningful observations. The analysis for each metric of interest can happen at either the degree enrollment level (using measurements for each learner in each program) or the course enrollment level (using measurements for each learner in each course). Tables of covariates used for each of these analyses are provided in the next section of the appendix.

Because of the vast diversity of learners and instructional design choices within degree programs hosted on Coursera, there are many potential confounding variables that make it challenging to estimate the true impact of some of these drivers on the outcome that we care about. There are five main categories of variables that we use:

- Student variables are generally variables that are fixed characteristics of a learner like age or nationality
- Course variables are generally variables that are fixed for a given course within a program, such as the number of staff-graded assessments
- Program drivers are captured within our analysis as program fixed effects
- Course Enrollment variables are those which arise from the interaction of a learner with course material. For example, this might be the number of assessments that a learner turns in
- Program Enrollment variables are those which arise from the interaction of a learner with a degree program overall. These include features such as the number of courses that stack into a degree program that a learner took before enrolling in the program

With a large set of control variables (many of which are categorical and require the specification of many levels), we use double-lasso for principled covariate selection with a separate model for each driver to ensure that our estimate of its impact is as reliable as possible. Because we are analyzing each driver in its own model, we make a couple of key assumptions in order to compare their relative impact on the same scale.

First, we assume that all drivers have a linear, additive effect on the outcome metric when controlling for the selected covariates. This is often an over-simplification but allows us to make relative comparisons between differently-distributed metrics much more easily. Second, we report the impact of each driver as the percent difference in model predictions when the driver variable is perturbed from its 25th percentile to its 75th percentile, holding all control variables at their true distribution in the dataset. This can effectively be thought of as the average impact that a driver has on an outcome metric when it is changed from the lower end of its distribution to the higher end. We believe that these alterations fall in the range of reasonable actions that either instructors or learners can take to enhance the quality of the learning experience.

Detailed Table of Potential Controls

Table 1 Controls for Learner Analyses

Category	Variable	Variable Definition
Program	Degree Program	Fixed Effect for the Degree Program
Program	Number of terms allowed missing	The number of terms in a program that are allowed to be missed by a learner.
Program	Distribution of Course Load	Distribution of course load within a program (quartiles and interquartile range of the number of courses enrolled)
Program	Number of Terms per Year	Number of terms in a program including controls for required and non-required terms.
Program Enrollment	Terms Since Admitted	The number of terms between when the learner was admitted and when they started the degree program.
Program Enrollment	Season	Whether the term is in the spring, fall or summer
Program Enrollment	Courses Enrolled	The number of courses a learner enrolled in within a given term.
Program Enrollment	Courses Dropped	The number of courses a learner dropped within a given term.
Program Enrollment	Courses Dropped after Deadline	Whether a student dropped a course after the drop deadline.
Program Enrollment	Support Tickets	Whether a learner files a support ticket of various different types during a given term.
Program Enrollment	Open Content Enrollments	Student has enrolled in open content on the Coursera platform.
Program Enrollment	Open Content Paid Enrollments	Student has enrolled in paid enrollments in open content on the Coursera platform.
Program Enrollment	Open Content Completions	Student has completed open content on the Coursera platform.
Program Enrollment	Stackable Content Enrollments	Student has enrolled in open content on the Coursera platform that stacks into the degree program.

Program Enrollment	Stackable Content Completions	Student has completed open content on the Coursera platform that stacks into the degree program
Student	Country Group	Student's nationality grouped by region
Student	Age	Student's age at degree start
Student	Education Level	Student prior educational background
Student	Registration Timing	Whether the learner was a long-time Coursera learner or registered on the platform shortly before the start of their degree program.

Table 2 Controls for Instructional Design Analyses

Category	Variable	Variable Definition
Assignment Types	Assignment Type Indicators (7 variables)	Indicator of whether the course contains at least one assignment of the given type: quiz, staff-graded assignment, peer-graded assignment, programming assignment, plug-in, discussion prompt
Assignment Types	Assignment Type Prevalence (7 variables)	Fraction of graded assignments in the course of the given type: quiz, staff-graded assignment, peer-graded assignment, programming assignment, plug-in, discussion prompt
Assignment Types	Assignment Type Grading Weight (7 variables)	The fraction of student grade attributable to assignments of the given type: quiz, staff-graded assignment, peer-graded assignment, programming assignment, plug-in, discussion prompt
Assignment Types	Late Penalty Prevalence	The fraction of graded assignments with late penalties
Assignment Types	Graded Assignment Group Prevalence	The fraction of graded assignments that are part of graded assignment groups (only the highest grades count for final grade calculation)
Assignment Types	Maximum Grading Weight	The largest fraction of the student grade attributable to a single assignment
Assignment Types	Small/Medium/Large Assignment Weight Prevalence	The fraction of graded assignments that accounted for a certain weight in the final grade calculation: 0-5% (small), 5-15% (medium), 15%+ (large)
Content Types	Content Type Prevalence (4 variables)	The fraction of non-graded items in the course of the given type: videos, readings, practice assignments, other
Course Characteristics	Fraction of terms offering course	The fraction of past terms in the program that offered the course

Course Characteristics	Item Count	The total number of items (lectures, readings, assignments, etc.) in the course outline
Course Characteristics	Assignment Count	The number of graded assignments in the course outline
Course Characteristics	Week Count	The number of weeks of content in the course outline
Course Characteristics	Video Time	The total video time (minutes) across the course
Weekly Pacing	Weekly content averages (6 variables)	The mean number of entities per week: videos, readings, practice assignments, graded assignments, video minutes, graded assignment total grading weight
Weekly Pacing	Weekly content coefficients of variance (6 variables)	The standard deviation number of entities per week divided by the mean number of entities per week: videos, readings, practice assignments, graded assignments, video minutes, graded assignment total grading weight
Weekly Pacing	Weekly learning time average	The mean of learning minutes (inferred from logs of on-platform course progress) required per week by the average student
Weekly Pacing	Weekly learning time coefficient of variance	The standard deviation of learning minutes required per week by the average student divided by the mean number of learning minutes required by the average student
Weekly Pacing	Content centroid (5 variables)	The midpoint of all the entities across the weeks of the course, divided by the number of weeks in the course: graded assignment total weight, video minutes, average learning time, graded assignments, practice assignments Example: A 4-week course has the following outline: • 0% of course grade due in week 1 • 25% of course grade due in week 2 • 25% of course grade due in week 3 • 50% of course grade due in week 4 Graded assignment total weight centroid = (0*1 + 0.25*2 + 0.25*3 + 0.5*4)/4 = 0.8125
Weekly Pacing	First week video time	The total video time (minutes) in the first week of the course
Forum Activity	Total Days Accessing Forums	The unique number of days that the student accessed the course forum
Forum Activity	Total Days Posting in Forums	The unique number of days that the student posted a thread or a reply in the course forum
Forum Activity	Total Forum Threads Initiated	The total number of forum threads initiated by the student in the course forum
Forum Activity	Total Forum Replies	The total number of forum thread replies posted by the student in the course forum

Student Activity	Learning Hours (3 variables)	The cumulative sum of learning time for the student in the course across various time durations: before the first assignment deadline, before the midway point in the course, across the entire course
Student Activity	Days Active (3 variables)	The cumulative sum of unique days on which the student completed at least one learning task (watched lecture, viewed reading, completed assignment, etc.) in the course across various time durations: before the first assignment deadline, before the midway point in the course, across the entire course
Student Activity	Fraction of assignments submitted pre-deadline (3 variables)	The fraction of graded items (weighted by contribution to the final course grade) that the student submitted before the assignment deadline, calculated across various points during the course: at the first deadline, at the midway point in the course, on the last deadline in the course
Student Performance	Grade Achieved	The final grade that the student earned in the course

About the Teaching & Learning Team at Coursera

The Teaching & Learning team is comprised of learning science and instructional design experts who drive the creation of transformational learning experiences. The team empowers partners, clients, and vendors in best-practice content creation through training, consulting, and quality assurance. In addition, T&L experts conduct pedagogy research to infuse the platform and products with learning innovations.

About the Data Science Team at Coursera

The Data Science team at Coursera develops the statistical and machine learning models that power the learning experience, leads the experimentation and inference that informs Coursera's strategy, and builds the products to access data for the company's university partners and enterprise customers. The team has ideated and launched data products powered by machine learning covered in TechCrunch, Harvard Business Review, MIT Technology Review, and the World Economic Forum. See more of their work on the Coursera Data Blog.

About the Authors

Alexandra Urban is a Principal Learning Designer at Coursera. She focuses holistically on the content development process, improving the platform, and advancing online pedagogy to support the millions of learners on Coursera. Her background is in Educational Neuroscience, applying how the human brain learns to improve teaching environments. She is currently pursuing a doctorate degree in Mind, Brain, and Teaching from Johns Hopkins University to conduct large-scale research on better supporting female learners in online STEM courses.

Alan Hickey is a Data Science Manager at Coursera. He leads the data team focused on the learner and educator experience, spanning both decision science and data products. His team is responsible for identifying opportunities to drive learner engagement with new product features and measuring the impact of product launches and building data products to directly power the learning experience. He and his team track academic integrity and provide data tools to help instructors create high-quality courses and support their millions of learners at scale.

Eric Karsten is a Senior Data Scientist at Coursera. He works on Coursera's Skills Graph team, using the common language of skills to build a deep understanding of how education bridges the gap between learners and their career objectives. He uses causal inference techniques to guide product development of machine learning data products. He also leads the Insights and Research vertical, partnering with external university and NGO researchers to use Coursera's data to answer questions about skills and labor markets. His work has been included in publications from the World Economic Forum. Eric holds an MA in economics and a BA in mathematics, both from the University of Chicago.